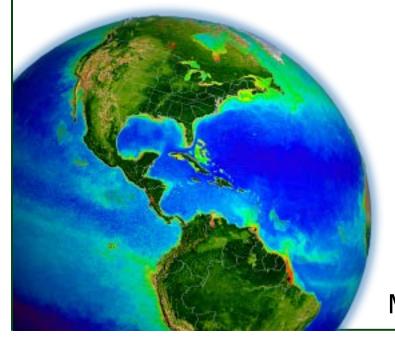
Remote Sensing Reflectance and Derived Products: MODIS and VIIRS



Bryan Franz
Ocean Ecology Laboratory
NASA Goddard Space Flight Center

MODIS/VIIRS Science Team, 15-19 October 2018, Silver Spring, MD



Project Team

MODIS Algorithm Maintenance Remote Sensing Reflectance, Chlorophyll, Diffuse Attenuation

Science of Terra/Aqua/SNPP

Advancing the Quality and Continuity of Marine Remote Sensing Reflectance and Derived Ocean Color Products from MODIS to VIIRS

Team Member	Role
Bryan Franz (PI)	Project lead
Amir Ibrahim (Co-I)	Atmospheric correction
Sean Bailey (Co-I)	Vicarious calibration
Gerhard Meister (Co-I)	Instrument calibration
Jeremy Werdell (Co-I)	Bio-optical algorithms
Zia Ahmad (Supp)	AC & radiative transfer code
Gene Eplee (Supp)	Instrument calibration (VIIRS)
Shihyan Lee (Supp)	Instrument calibration (MODIS)
Chris Proctor (Supp)	In situ validation
Erdem Karakoylu (Supp)	Uncertainties

and the Ocean Biology Processing Group



Contents

1. Status of MODIS & VIIRS Ocean Color Products

2. Status and Plans for Algorithm Advancement

- 1. Multi-band Atmospheric Correction
- 2. Rrs Uncertainty Product



Ocean Color Reprocessing R2018.0

Completed

Dec 2017 (VIIRS/SNPP), January 2018 (MODIS/Aqua), April 2018 (MODIS/Terra)

Purpose

- incorporate updates to vicarious calibration due to revised MOBY time-series
- incorporate updates to instrument calibration
- no algorithm changes



Impact of MOBY Revisions on MODISA Ocean Color

Global Deep Water Time-Series Test (MOBY change only)

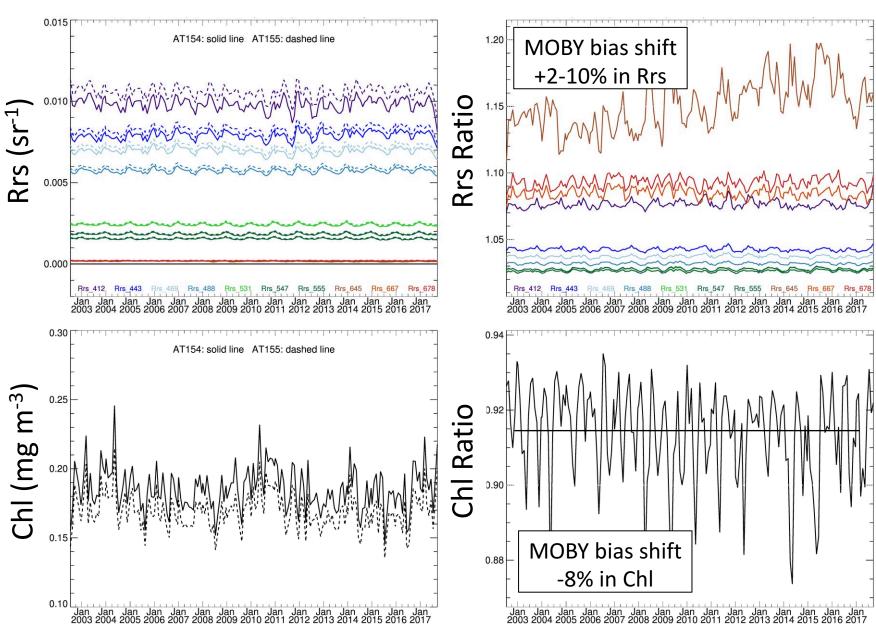
MOBY in situ radiometry is used for vicarious cal of visible bands, all missions

MOBY reprocessed by MOT in 2016 and 2017

- revised depth of sensor arms
- new straylight correction

Impact was to

- increase Rrs by 2-10%
- decrease global Chl by 8%





MODISA Instrument Calibration Update

Goal was to mitigate some temporal artifacts observed in previous ocean color trends, believed to be associated with cal data smoothing/fitting decisions.

Complete end-to-end re-analysis of on-board calibration was performed, largely following MCST approach, but with some differences.

- SD/SDSM screens, SD BRF: derived from simple fit of yaw maneuver data, not geometric modeling
- SDSM Cal: SD degradations in red/NIR were determined by wavelength modeling (Lee et al., 2018)
- RVS: simple atmospheric correction added when computing desert trends to track RVS in 412, 443nm
- Modulated RSR: impact on ocean data estimated and used to adjust 412nm temporal gains (Lee et. al. 2017)
- RSB LUTs: use of smoothing rather than fitting to the instrument temporal calibration trending and characterization (i.e., no assumption on functional form)

Monthly update to maintain calibration trend consistency in forward processing.

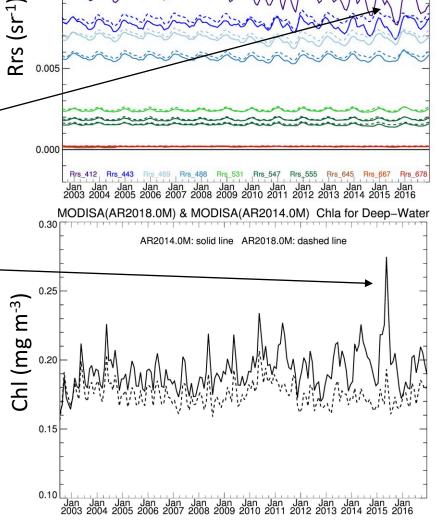


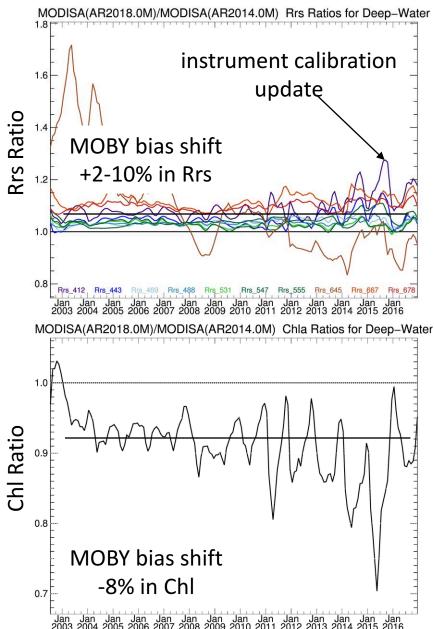
MODISA Global Deep-Water (R2018.0 vs R2014.0)

MODISA(AR2018.0M) & MODISA(AR2014.0M) Rrs for Deep-Water



Large seasonal spikes in chlorophyll removed.



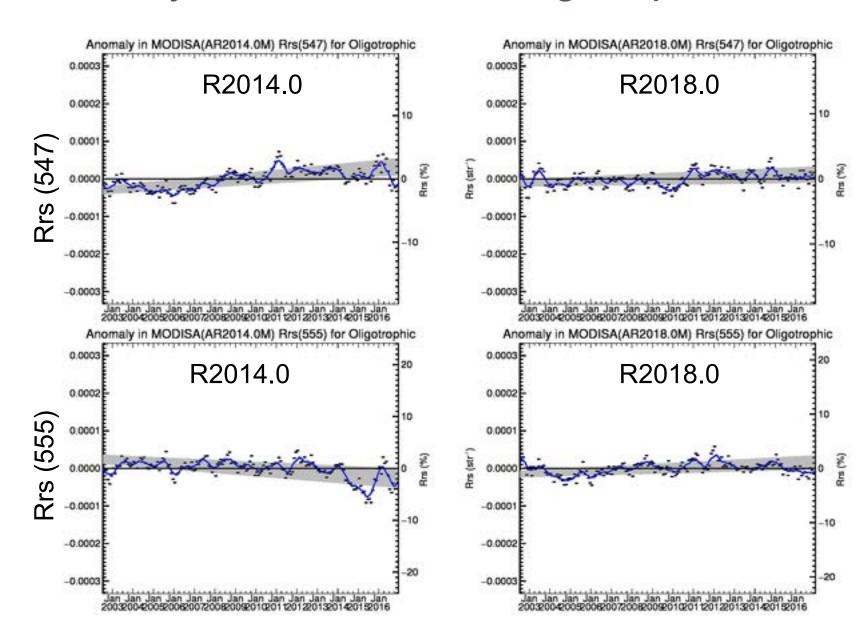




MODISA Rrs Anomaly Trend in Global Oligotrophic Water

In very clear-water, open ocean regions (Chl < 0.1), we expect minimal variability in green spectral bands.

R2018 shows improved stability in temporal trends of water-leaving reflectance in the green bands of MODIS/Aqua.

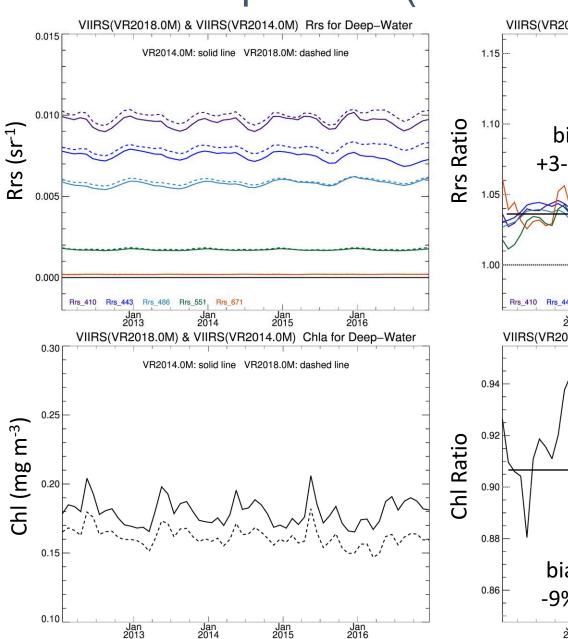


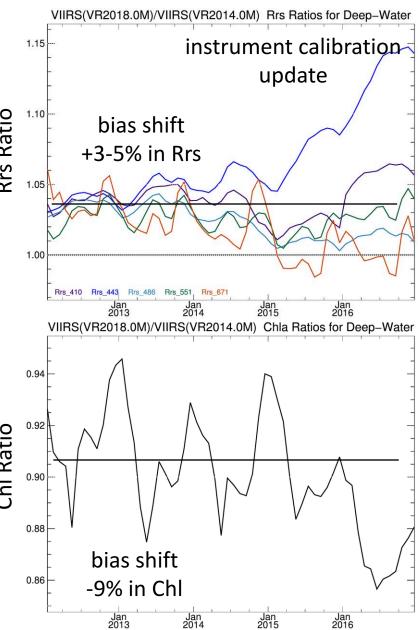


VIIRS/SNPP Global Deep-Water (R2018.0 vs R2014.0)

Instrument Calibration updates include:

- revised temporal cal with additional solar & lunar measurements since R2014
- lunar measurements corrected for detector gain variability
- absolute calibration of all spectral bands based on observations of the sun through the solar diffuser

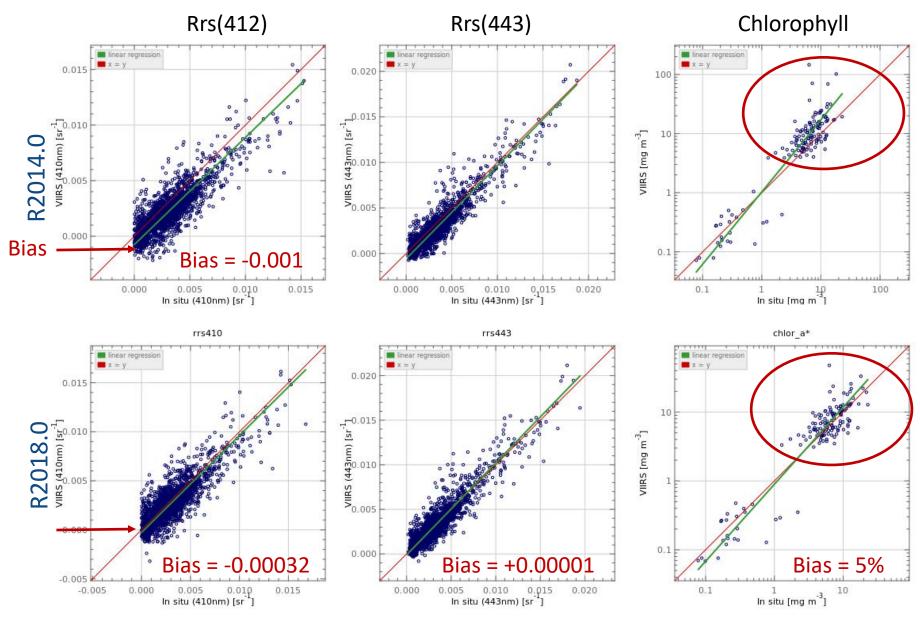






VIIRS/SNPP R2018.0 Reprocessing

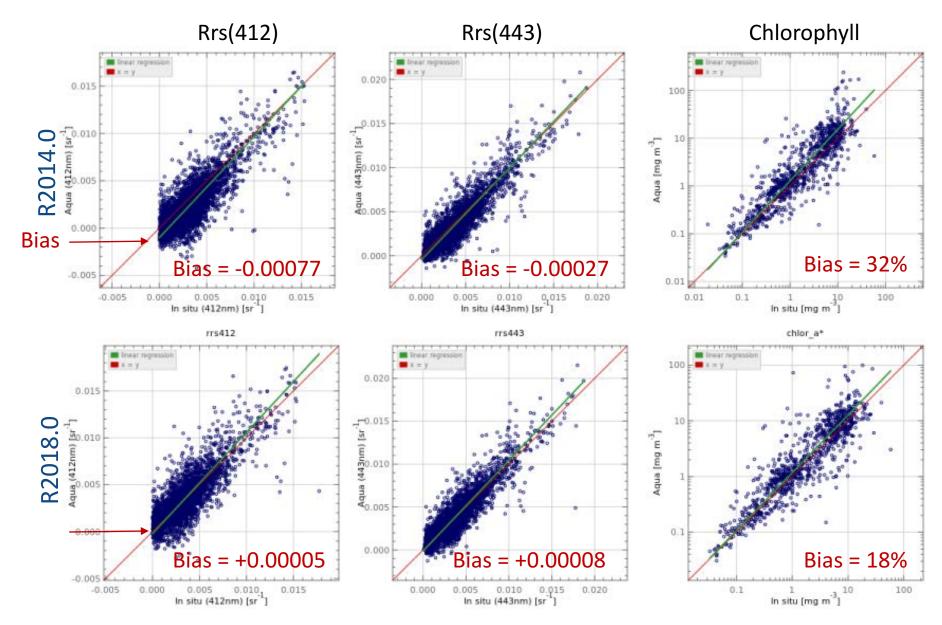
improved agreement with in situ





MODISA R2018.0 Reprocessing

improved agreement with in situ





In situ Rrs Match-up Statistics for MODISA

- equal or reduced mean bias and MAE in all bands
- large negative bias in blue reduced to small positive bias

Product	Number	Mean B	ias (sr ⁻¹)	Mean Absolute Error (sr ⁻¹)		
	Matchups	R2014.0	R2018.0	R2014.0	R2018.0	
Rrs(412)	3934	-0.00077	0.00005	0.00125	0.00099	
Rrs(443)	4134	-0.00027	0.00008	0.00082	0.00075	
Rrs(488)	3772	-0.00067	-0.00050	0.00088	0.00077	
Rrs(531)	2076	-0.00063	-0.00057	0.00083	0.00079	
Rrs(547)	3619	-0.00052	-0.00048	0.00078	0.00076	
Rrs(555)	3534	-0.00081	-0.00075	0.00096	0.00090	
Rrs(667)	3573	-0.00017	-0.00016	0.00030	0.00029	
Rrs(678)	472	-0.00016	-0.00014	0.00034	0.00033	

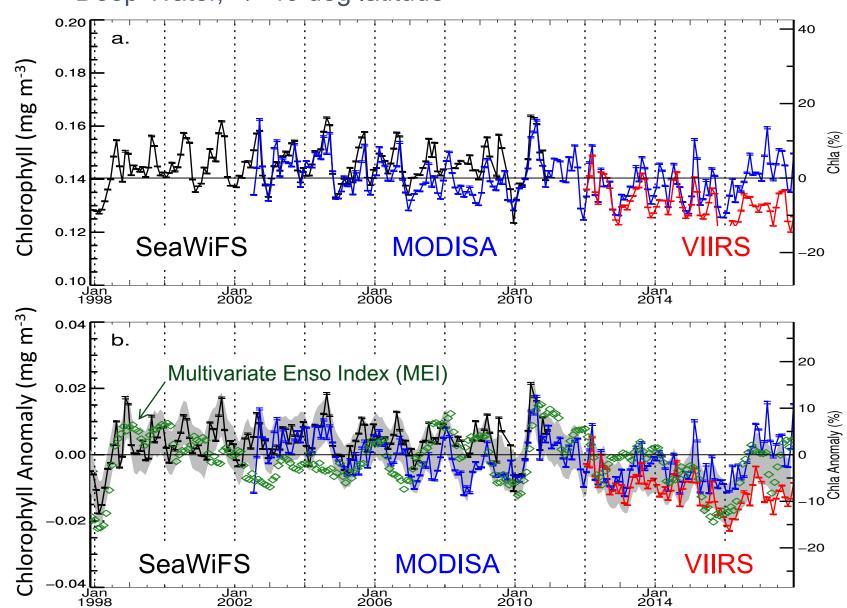
identical field data sources from AERONET-OC and SeaBASS



21-year Multi-mission Chlorophyll Timeseries

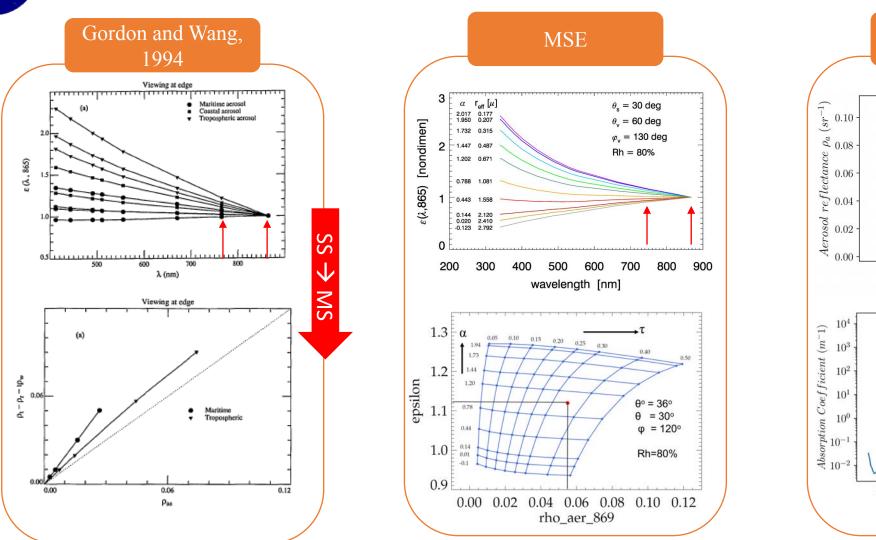
Deep-Water, +/- 40 deg latitude

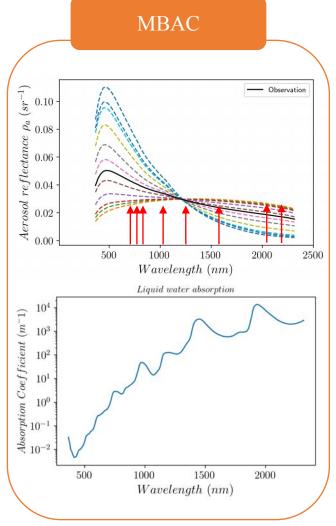
- MODISA in good agreement with SeaWiFS and VIIRS (through ~2015)
- anomaly trends generally consistent with expectations based on MEI
- suspect late mission trend in VIIRS (did not recover from 2015/16 ENSO event)
- likely issue is unresolved impacts in blue bands to changing spectral response of VIIRS (TBD)



NASA

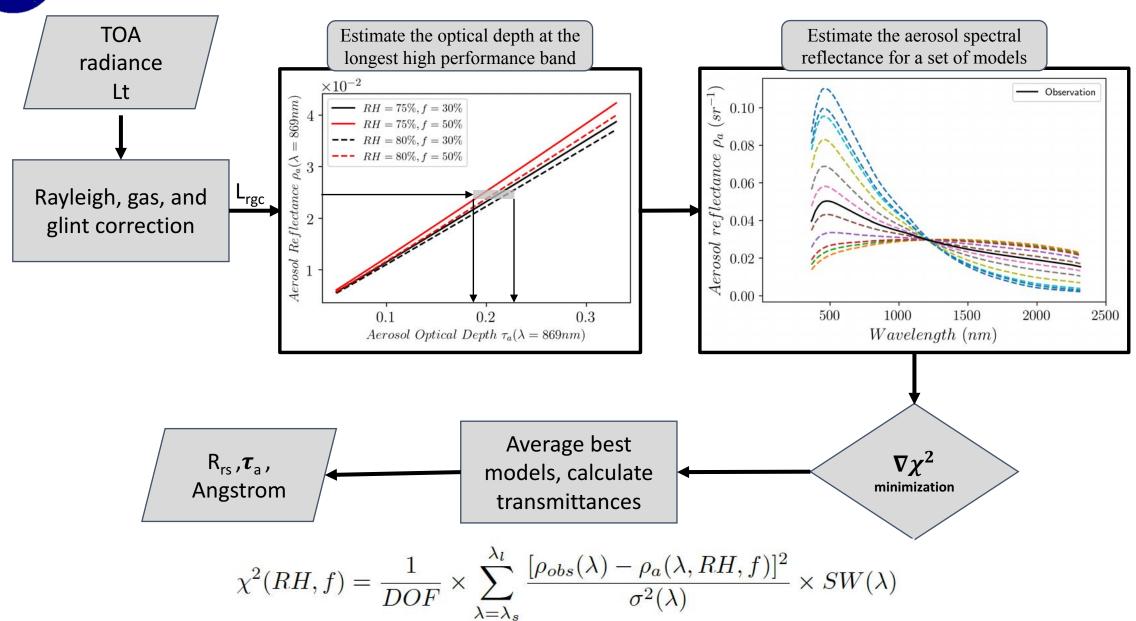
AC Algorithm Refinement





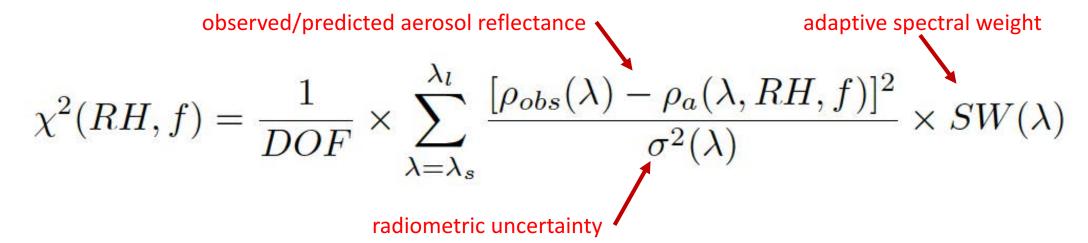
NASA

Multi-band Atmospheric Correction (MBAC)

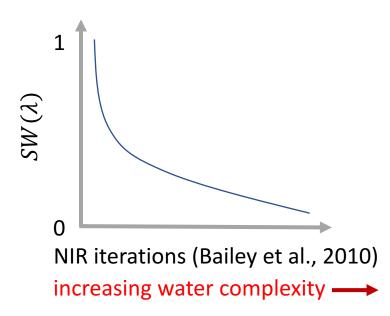




MBAC Cost Function

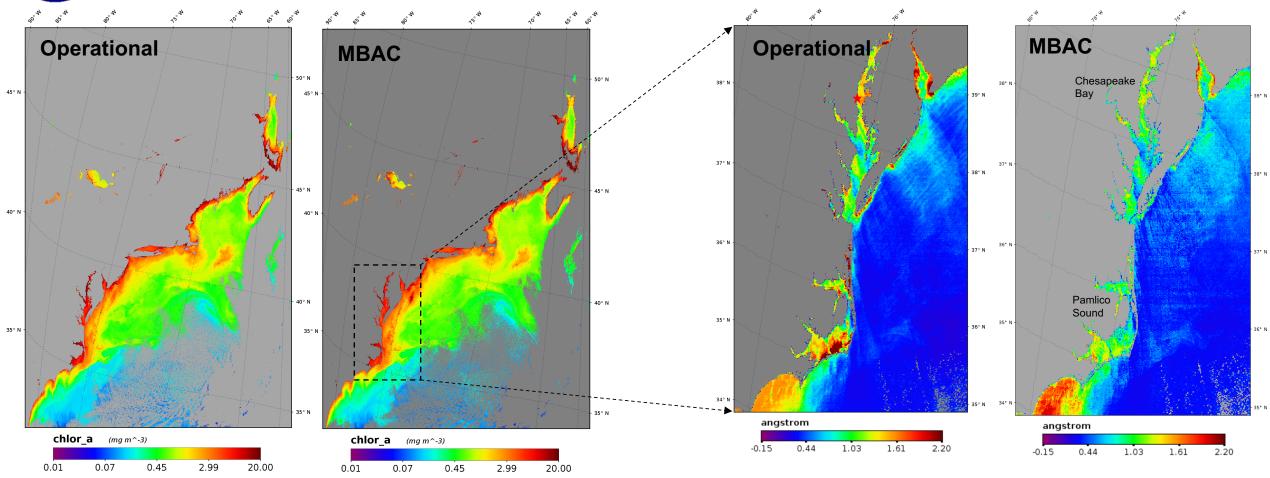


Sensor	Wavelength (λ , nm)							
MODIS	748	859	869		1240	1640	2130	
VIIRS	746	868			1238	1604		2258
PACE-OCI	750	860	870	1038	1250	1615	2130	2260





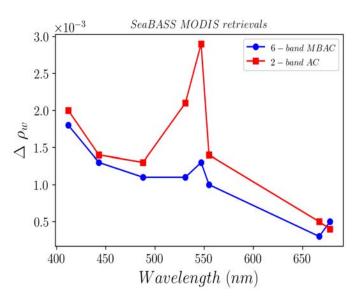
Application to MODISA (MBAC vs Std AC)



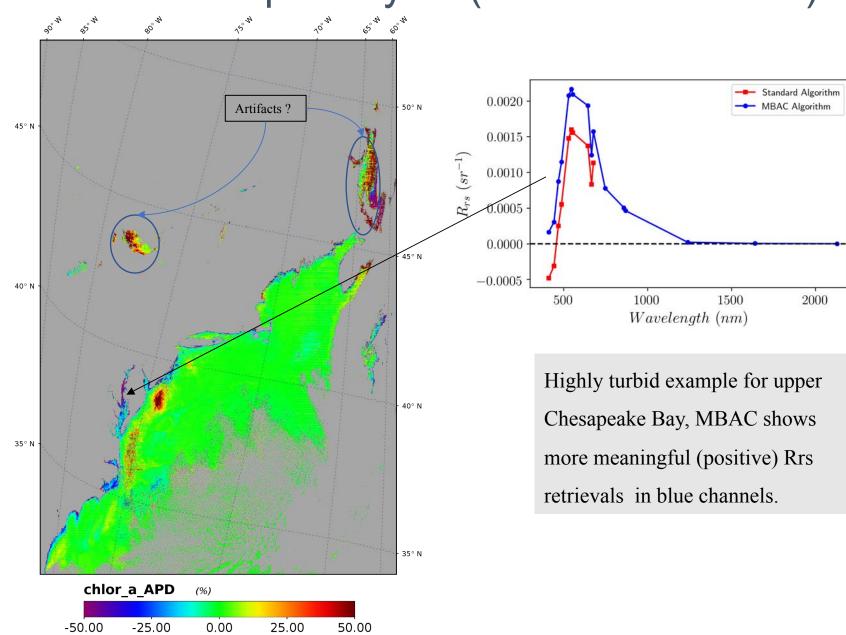
- MBAC chlorophyll retrievals similar to standard algorithm, except in turbid coastal regions.
- Difference is due to retrieved aerosol models (aerosol type).



MODISA In Situ Match-up Analysis (MBAC vs Std AC)



SeaBASS in-situ matchups to water-leaving reflectance shows reduction in error using MBAC relative to standard algorithm, at all spectral bands.

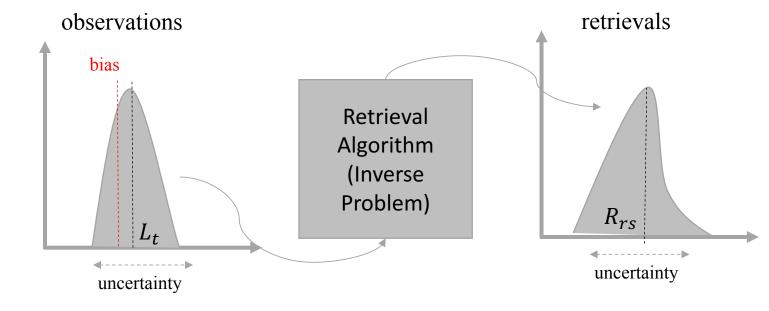




Development of a Per-Pixel $Rrs(\lambda)$ Uncertainty Product



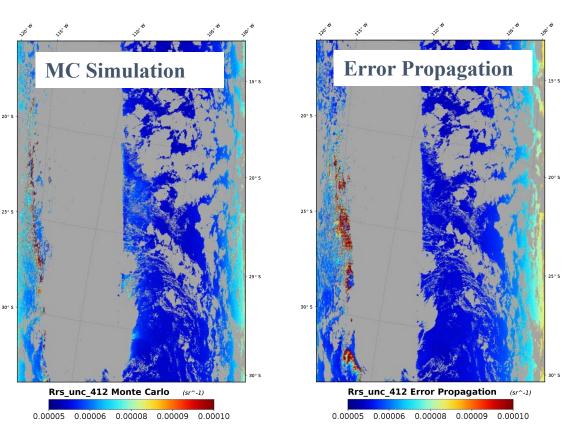
- Sensor Random Noise
- Sensor Systematic Noise





Sensor Random Noise

- Sensor noise can be propagated through the MSE/MBAC algorithms using standard error propagation.
- Results agree very well with MC simulations (presented previously).



Uncertainty per-pixel

Step-by-step error propagation

$$\frac{\partial R_{rs}(\lambda)}{\partial R_{rs}(\lambda)} = \frac{\partial L_{t}(\lambda)}{\partial L_{t}(\lambda)} \times \sqrt{\left[\frac{BRDF(\lambda)}{T_{g0}(\lambda) \times F_{0}(\lambda) \times f_{0} \times \mu_{0}}\right]^{2} \times \left[\frac{\partial L_{w}^{2}(\lambda)}{L_{w}^{2}(\lambda)} + \frac{\partial t_{0}^{2}(\lambda)}{t_{0}^{2}(\lambda)} - 2\rho_{t_{0},L_{w}}(\lambda) \times \frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{t_{0}(\lambda) \times L_{w}(\lambda)}}\right]}$$

$$\frac{\partial R_{rs}(\lambda)}{\partial L_{w}(\lambda)} = \frac{\partial L_{t}(\lambda)}{\partial L_{w}(\lambda)} \times \frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)} + \frac{\partial L_{w}^{2}(\lambda)}{\partial L_{w}(\lambda)} + \frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)} \times \frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)}$$

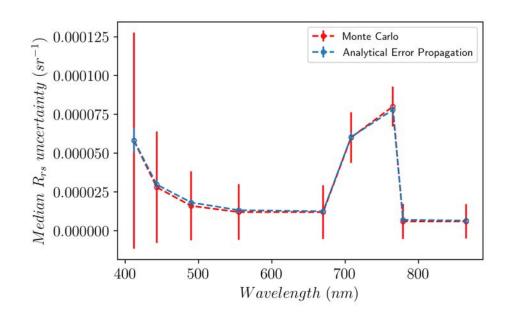
$$\frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)} \times \frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)} \times \frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)} \times \frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)}$$

$$\frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)} \times \frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)} \times \frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)} \times \frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)}$$

$$\frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)} \times \frac{\partial L_{w}(\lambda)\partial t_{0}(\lambda)}{\partial L_{w}(\lambda)}$$

$$\partial L_w(\lambda) = \partial L_t(\lambda) \times \sqrt{\frac{\partial A^2(\lambda)}{A^2(\lambda)} + \frac{\partial t^2(\lambda)}{t^2(\lambda)} - 2\rho_{A,t}(\lambda) \times \frac{\partial A(\lambda)\partial t(\lambda)}{A(\lambda) \times t(\lambda)}}$$

$$(A(\lambda)) = -L_t(\lambda)/T_g(\lambda) + L_r(\lambda) + [L_a(\lambda) + L_{ra}(\lambda)] + t(\lambda)L_f(\lambda) + TL_g(\lambda)$$



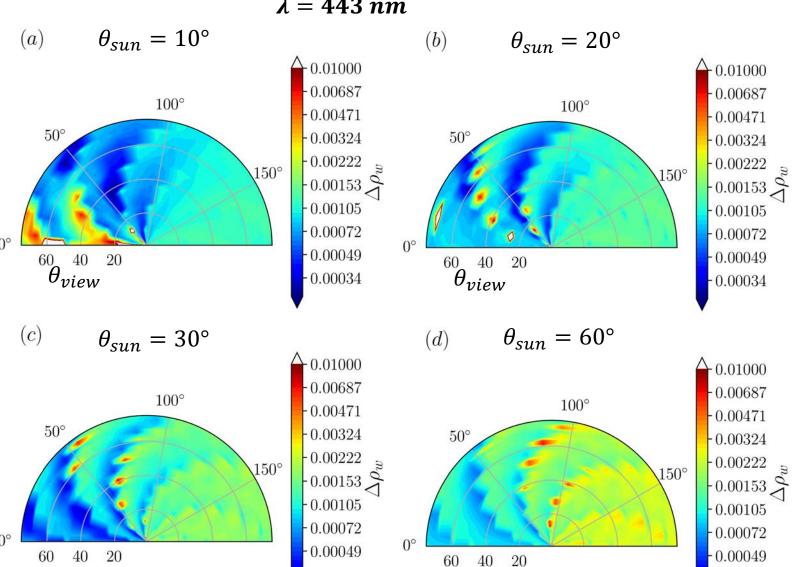


Algorithm Uncertainty

Simulation parameters:

- $\theta_{view} = 0^{\circ}: 80^{\circ}$,
- $\Delta \varphi = 0^{\circ}: 180^{\circ}$
- $\theta_{sun} = 10^{\circ}, 20^{\circ}, 30^{\circ}, 60^{\circ}$
- $\tau_a = 0.05:0.35$
- $RH = 77.5\% \rightarrow Not in the LUT$
- f = 0:0.95
- chlor-a = 0.03 mg/m^3
- total # cases: 1037400
- average $\Delta \rho_{w}(443) = 0.0015$
- uncertainty increases with solar zenith angle
- uncertainty increases significantly for larger fine-mode fraction cases due to the linear-mixing limitations

$\lambda = 443 nm$



 θ_{view}

-0.00034

-0.00034

 θ_{view}



Sensor Systematic Error

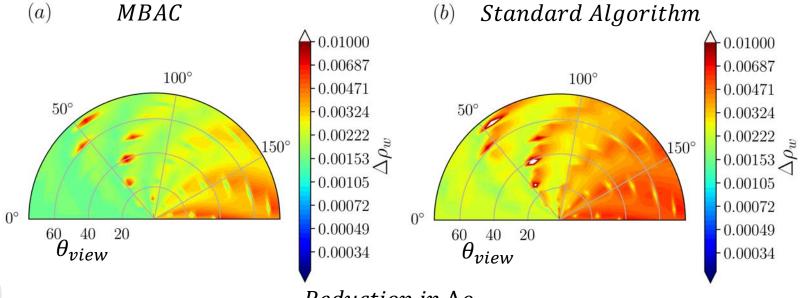
$\lambda = 443 \ nm$, $\theta_{sun} = 30^{\circ}$

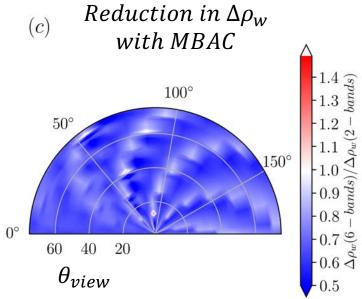
Simulation parameters:

- classical covariance analysis
- assume correlated bias of 2% on bands
 >750 nm and 0.5% on VNIR bands
- assume 10% correlated covariance between bands

average uncertainty:

- Operational 2-band AC \rightarrow 0.0036
- MODIS-MBAC 6-band $\rightarrow 0.0024$
- Uncertainty is reduced by \rightarrow 34%







Future Development

Multi-Band Atmospheric Correction

- assess/improve spectral-relative calibration for NIR/SWIR region (MODIS & VIIRS)
- assess/improve performance of adaptive weighting scheme
- initiate global-scale testing for MODIS & VIIRS

Rrs Uncertainty Product

- complete the algorithm framework for Rrs uncertainty product (combined random/systematic/algorithm error)
- refine systematic error terms for each instrument
- assess uncertainty estimates relative to match-up results (closure experiment)

Instrument Calibration

- reassess VIIRS spectral response changes, impact on trends in blue
- evaluate MODIS-Terra R2018.0 results